Geospatial analysis of behavior, duration and severity of drought over Paraíba State, northeastern Brazil

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Abstract: Droughts threaten water resources, agriculture, socio-economic activities and the population at the global and regional level and identifying areas with homogeneous behaviors regarding the action of these phenomena is a relevant issue that contributes to the management of water resources. The objective of this study is to identify homogenous zones over Paraíba State as to the behavior, duration and severity of droughts that occurred over the last 20 years (1998–2017) using hierarchical cluster analysis based on rain gauge-measured and Tropicall Rainfall Measuring Mission (TRMM) estimated rainfall data. The drought series were calculated using Standardized Precipitation Index (SPI) based on eight time scales and were grouped according to behavior, duration and severity time series. The integrated results of behavior, duration and severity of droughts indicate that there is a tendency to divide Paraíba State into two major regions (a) Zone I, formed by Mata Paraibana and Agreste Paraibano, and (b) Zone II, composed by Borborema and Sertão Paraibano. This division is evident when assessing short-term droughts, but in the case of long-term droughts, Paraíba State has high similarity in terms of drought behavior, duration and severity. Factors such as proximity to the ocean, active climatic systems and the configuration of the local relief were identified as influencing the drought regime. Finally, it is concluded that the rainfall estimates of the TRMM satellite represent a valuable source of data to regionalize and identify the drought pattern over the region and that other studies of this type should be carried out to monitor these phenomena based on satellite data.

Keywords: SPI; remote sensing; satellite data; rainfall; semiarid region

1. INTRODUCTION

Precipitation has a substantial role on the Earth's energy balance, in the dilution of water salinity near the sea surface and the wet deposition of air pollutants and aerosols in the lower atmosphere. Also, as an important indicator of global and regional climate change (Singh and Qin, 2020), precipitation is an important variable for climate and runoff (Chu et al., 2020). In addition, the spatiotemporal variability of precipitation is a direct result of global and regional changes in the climate system, and this variability is correlated with changes in the hydrological cycle (Fu et al., 2017). For example, in wetlands areas, excessive precipitation generally causes floods, but in arid and semiarid regions, the lack of precipitation causes meteorological droughts (Guntu et al., 2020).

The future impacts of climate change for semiarid regions can cause the intensification and prolongation of droughts, in addition to generating serious problems, such as water scarcity and collapse in the water supply (Li et al., 2020). Droughts can also cause socio-environmental impacts of various magnitudes, such as desertification, reduction of agricultural potential and the rural exodus (Vieira et al., 2020). Drought events in the semiarid region are frequent, and are expected to increase in frequency and severity in the coming decades (IPCC, 2014). Therefore, precipitation measurements are essential for water resources monitoring in regional or global climate changes (Mossad and Alazba, 2018).

Actually, many developing or less developed countries have problems in collecting and storing high-quality and long-term meteorological data due to limited financial resources, which is especially difficult in arid and semiarid regions (Tan, 2019). Therefore, satellite precipitation products are used as an alternative source to study the climate system in large or in non-instrumented watersheds (Tan and Duan, 2017). Among them, the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) (Huffman et al., 2007; Liu et al. 2012) is one of the precipitation products that contains daily long-term records of precipitation with acceptable accuracy in various regions of the globe (Qin et al., 2014; Prakash et al., 2015), which reliability has been widely evaluated in the aspects of general measurement of precipitation (AL-Falahi et al., 2020), hydrological modeling (Ur Rahman et al., 2020; de Medeiros et al., 2019; Silva et al., 2018) and drought analysis (Ferreira da Silva et al., 2020; Suliman et al., 2020; Brasil Neto et al., 2020; Liu et al. 2010).

However, further studies are still needed to analyze the quality of the TRMM rainfall products in the identification of behavior, duration and severity of droughts for different regions (dry and wet), as is the case of Paraíba State.

Paraíba State region has different climatic and geomorphological characteristics that control the spatio-temporal distribution of rainfall and for this reason, Paraíba State can be considered a good region to assess the performance of TRMM in the analysis of drought monitoring in different climatic zones. Specifically, Paraíba State is a region with different characteristics related to relief, vegetation and precipitation (Santos et al., 2019a), which makes monitoring precipitation and droughts on more detailed space-time scales a complex task. Moreover, several studies indicate that this region has recently been hit by one of the most severe drought events of the last years, and this has caused several damages to the population of the state (Marengo et al., 2017; Santos et al., 2019b).

To monitor the behavior, duration and severity of droughts, several rates have been developed (RajKhatiwada and Pandey, 2019). These indices integrate various variables such as, precipitation, temperature, flow, evapotranspiration, and humidity, and can be interpreted on a severity scale (normal, wet, medium or dry) to provide a comprehensive view of this phenomenon for decision making. However, each drought index has different characteristics and are suitable for specific environments (Zhang et al., 2017), a factor that stimulated several comparisons of different indexes in the literature in different climatic regions of the planet. Studies of this nature are scarce in Paraíba State because the hydrometeorological time series have many gaps, difficulting the analysis using different indexes (Santos et al., 2019b; Brasil Neto et al., 2020). In this context, the use of SPI is an important tool to assess the geospatial distribution of drought over Paraíba State, which is a predominantly semiarid region located in the Northeast of Brazil, one of the most vulnerable areas in the world due to climate change and where droughts are frequent (Dantas et al., 2020).

In other hand, identifying areas with similar characteristics to the occurrence of droughts is a useful but challenging task, as it involves the high knowledge of each region by the researchers. Thus, hierarchical cluster analysis methods have become notable as one of the most suitable instruments for defining pluviometrically homogeneous regions and their climate trends at regional and global level (Unal et al., 2003; Keller Filho et al., 2005; Lyra et al., 2014; Teodoro et al., 2016; Oliveira-Junior et al., 2017; Brito et al., 2017; Santos et al., 2019a). Droughts zoning based on the behavior, duration and severity of these phenomena is also a theme of interest of several studies (Rad and Khalili, 2015; Li et al., 2015; Wang et al., 2015; McGree et al., 2016; Shiau and Lin, 2016; Yang et al., 2017), but there is a lack of more detailed studies in the arid and semiarid regions.

The lack of studies that used cluster analysis to identify homogeneous regions based on the behavior, duration and severity of droughts at multiple time scales over the state of

Paraíba justify the importance of this work. Also, it is pointed out that droughts are natural disasters, and evaluating their behavior from a regional perspective is a relevant issue that can contribute to the management of water resources. Therefore, the objective of this study is to identify homogenous zones over Paraíba State as to the behavior, duration and severity of droughts that occurred over the last 20 years (1998–2017) using hierarchical cluster analysis based on rain gauge-measured and TMPA rainfall data.

2. MATERIAL AND METHODS

2.1 STUDY AREA

The study area is Paraíba State, with a total area of 56,469.78 km² and has a population of about four million inhabitants living in 223 municipalities (IBGE, 2016). Paraíba State is located between latitudes 5.875°S and 8.375°S and longitudes 38.875°O and 34.625°O (Figure 1). Paraíba State has a rectangular shape and is subdivided into four mesoregions, namely Mata Paraibana, Agreste Paraibano, Borborema and Sertão Paraibano (Figure 1). Its rectangular shape influences different factors that interfere with the circulation of winds and the climate of the region, standing out among these factors the proximity with Atlantic Ocean, the existence of plateaus, the mountain range and the depressions. Details about Paraíba State can be found in Santos et al. (2019a), Santos et al. (2019b) and Brasil Neto et al. (2020).

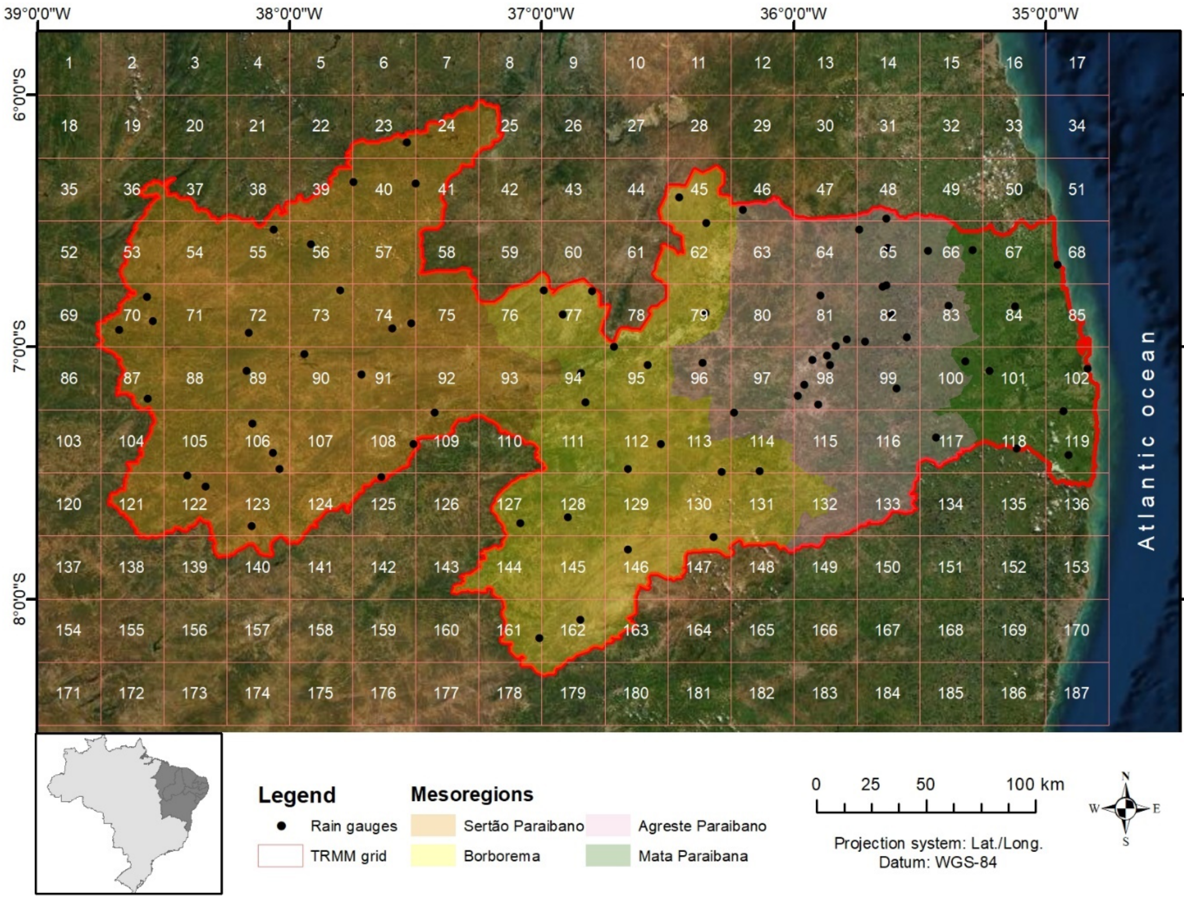

Figure 1. Location of Paraíba State, spatial distribution of the TMPA grid, the selected rain gauges, and its mesoregions.

2.2 RAINFALL DATASETS

2.2.1 IN-SITU MEASUREMENTS DATA

The rain gauge-measured data obtained over the period 1998 to 2017 were available by the Agência Executiva de Gestão de Águas (AESA). In all, there are 251 series spaced across the region, and daily data has been accumulated at a monthly level to calculate the SPI index. However, a previous analysis of the consistency of the rainfall time series available to assess the quality of the network over Paraíba State was carried out. All series that presented missing data were excluded from the following analyzes, resulting in 78 complete series to be used in the present study. More details regarding the qualitative and quantitative analysis of the available data can be found in Brasil Neto et al. (2020).

2.2.2 ESTIMATED RAINFALL DATASET

To carry out drought monitoring using complete and equally distributed satellite estimated rainfall data over Paraíba State, the Tropical Rainfall Measuring Mission (TRMM)

satellite datasets, which is a joint mission between the American Space Agency (NASA) and the Japanese Space Agency (JAXA), were used (Huffman et al., 2007; Liu et al. 2012). Launched at the end of 1997, the TRMM was developed to monitor rainfall in tropical regions but suffered technical problems around 2014 and started to fall slowly while continuing to collect data (Xia et al., 2018). Among the available ones, the TRMM Multi-satellite Precipitation Analysis (TMPA) (Huffman et al. 2007, 2010) is the product that combines the precipitation data estimated by remote sensing measurements from multiple satellites with the available observations of rain gauge for bias correction.

TMPA products cover extensive space domains, between latitudes 50°N and 50°S and longitudes 180°W and 180°E, with a refined spatial resolution of 0.25°× 0.25°, allowing the monitoring of rainfall in various areas of the globe (Huffman et al. 2007, 2020; Liu et al. 2012; Zhao et al., 2018). In Paraíba State, several studies have used TMPA estimates, and the results indicate that these estimates are viable alternatives concerning the development of environmental studies (Soares et al., 2016; Santos et al., 2019a; Santos et al., 2019b; Brasil Neto et al., 2020). In this work, data from TMPA 3B42v7 (TRMM 2011) were used, hereafter called TRMM, and the study area was divided into 187 grids (11 × 17). Figure 1 shows the spatial distribution of the TRMM cell grids and the rain gauges used in this work. The daily rainfall time series were accumulated at a monthly level from January 1998 to December 2017, totaling approximately 45,000 monthly rainfall data points (187 TRMM-estimated series × 20 years × 12 months) estimated by satellite.

2.3 SPI: RUN THEORY AND TIME SERIES DEVELOPMENT

The drought analysis from January 1998 to December 2017 were based on eight SPI multitemporal scales, i.e., (a) short-term droughts: SPI-1, SPI-3 and SPI-6, (b) medium-term droughts: SPI-9 and SPI-12, and (c) long-term droughts: SPI-18, SPI-24 and SPI-48. All eight-time scales were calculated by adjusting the precipitation data to a gamma distribution of two parameters α and β. The SPI series were calculated for each 78 rain gauge-measured data and the 187 TRMM-estimated time series. Details regarding the calculation of the SPI index can be found in Santos et al. (2017). In this study, each drought event was characterized by the continuity of dry events, i.e., SPI $\leq$ 0, based on the premise of Run Theory (Yevjevich, 1967).

Figure 2 illustrates the definition of a drought event and the behavior of the three time series evaluated in this study: (a) the behavior time series, (b) the drought duration time series (DDS), and (c) the drought severity time series (DSS). The DDS is the series that increases

incrementally during a drought event, and the DSS is the result of the accumulated SPI values during the drought event. For these two series, when the events are no longer dry (i.e., SPI ≤ 0), the series are null. The drought behavior series, in turn, reflects the SPI values themselves over time. In the case of the example in Figure 2, all three series are composed of 50 values.

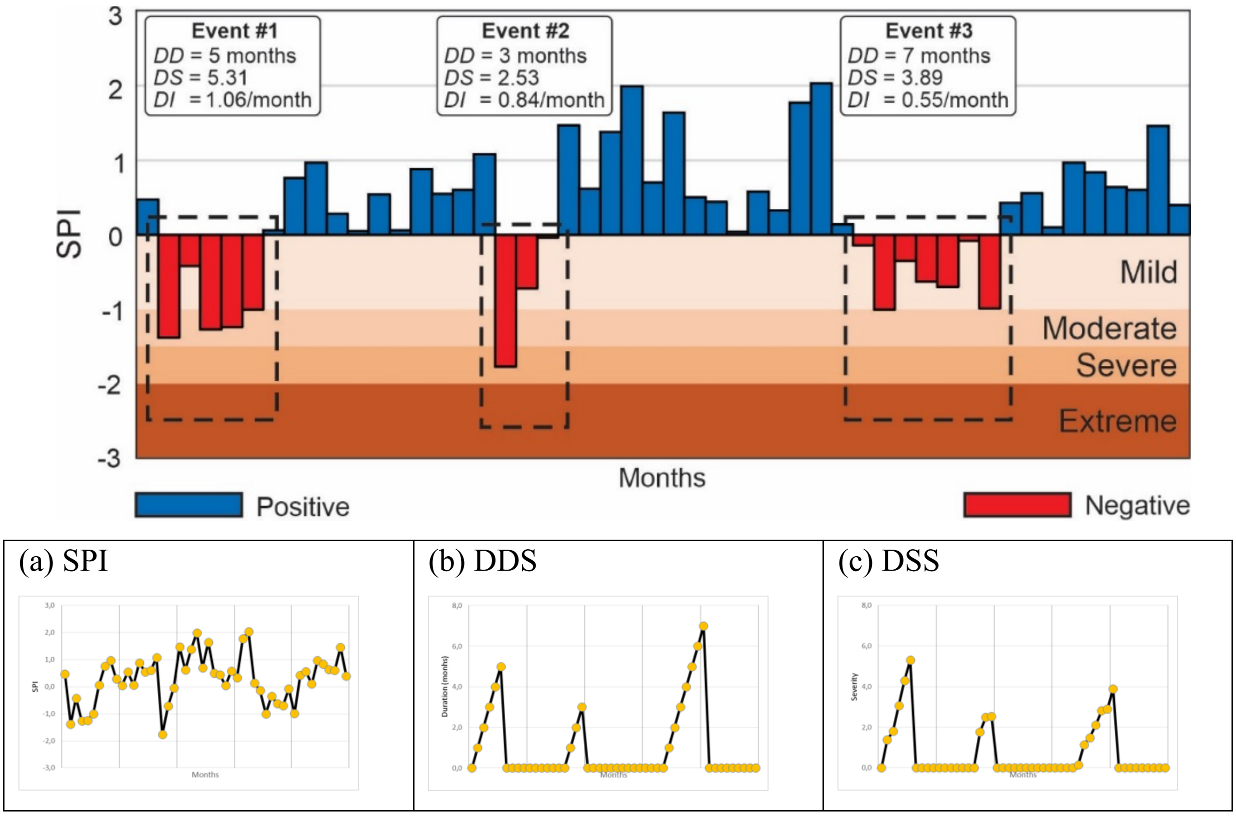

Figure 2. Definition of a drought event and its main characteristics.

2.4 CLUSTER ANALYSIS

Hierarchical cluster analysis techniques were used to regionalizate the Paraíba State in homogeneous regions based on drought behavior, duration and severity. The analyzes were performed for the eight time scales and considered the rain gauge-measured rainfall data and the satellite-estimated rainfall data, totaling 48 cluster analyzes (2 databases × 3 types series × 8 time scales). The basic steps of the hierarchical clusters analysis, such as choosing the metric of dissimilarity, the method of the linkage between clusters, and the optimal number of clusters (Keller Filho et al., 2005), were taken from statistical criteria, which guarantees the reliability of our results.

Regarding the dissimilarity metric, Pearson’s linear coefficient was calculated between the time series, considering that the time series will be grouped based on the similarity of their temporal variation. Thus, it was possible to evaluate how similar the behavior, duration and

severity time series in multiple time scales are over time, which is important information to assess the influence of the weather phenomena active in the region, for example. Equation 1 shows how the correlation distance between two different time series was calculated:

$$d = d(x_s, x_t) = 1 - \frac{\sum_{i=1}^{n}(x_s - \overline{x_s})(x_t - \overline{x_t})}{\sqrt{\sum_{i=1}^{n}(x_s - \overline{x_s})^2}\sqrt{\sum_{i=1}^{n}(x_t - \overline{x_t})^2}} \tag{1}$$

where d is the correlation distance between two time series x_s and x_t, $\overline{x_s}$ and $\overline{x_t}$ represent the averages of the historical series x_s and x_t that contain n data.

Then, we defined which linkage method was the most appropriate to perform the clusters analysis, and for that, the results were evaluated based on three different methods: single, complete and average. The single method considers the distance between the clusters the shortest distance between the elements; in the complete method, the largest distance between the components of different clusters is considered, and in the average method, the average of the distances between the series of cluster r with those of cluster s are taken into account. Figure 3 and Equation 3-5 illustrates the difference between the calculation of distances between two different clusters:

$$D(r, s) = m\acute{\imath}n(d(x_{ri}, x_{sj})) \tag{3}$$

$$D(r, s) = m\acute{a}x(d(x_{ri}, x_{sj})) \tag{4}$$

$$D(r, s) = \frac{1}{n_r n_s}\sum_{i=1}^{n_r}\sum_{j=1}^{n_s} d(x_{ri}, x_{sj}) \tag{5}$$

where $D(r, s)$ is the distance between clusters r and s, n_r is the number of components in cluster r, n_s is the number of elements in cluster s, d represents the metric of dissimilarity between the time series x_r and x_s, x_{ri} is component i of cluster r, and x_{sj} is element j of cluster s.

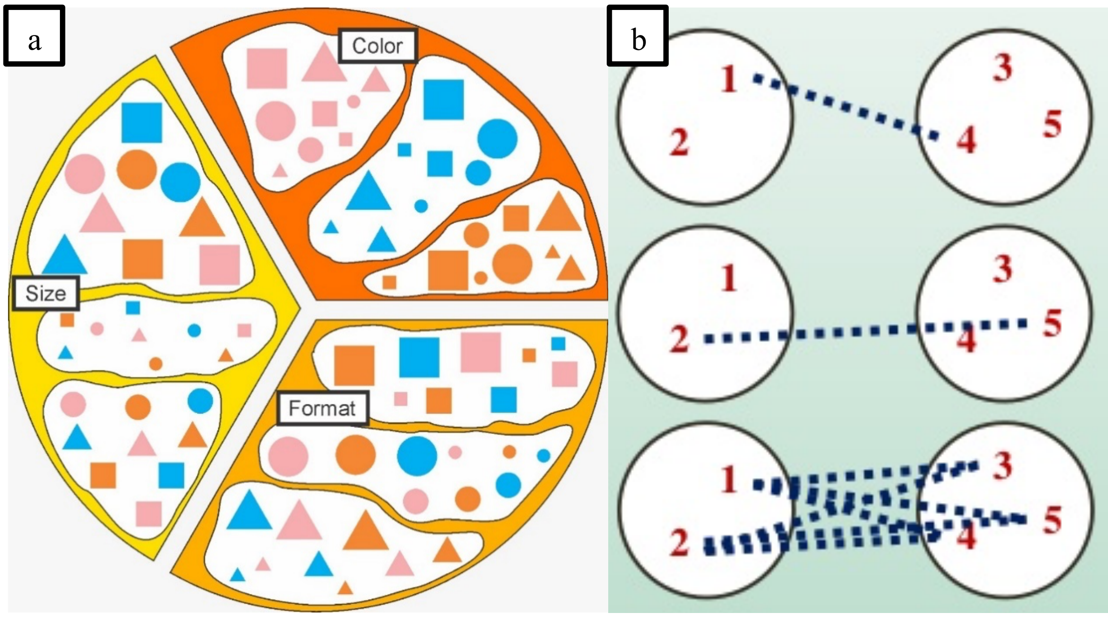

Figure 3. Influence of (a) dissimilarity metrics and (b) linkage method between clusters in the formation of different homogeneous groups. Each arrow represents the distance between the different clusters.

Additionally, the cophenetic correlation coefficient c was computed to assess the consistency and similarity of representativeness between the clusters. This coefficient measures how appropriate it was the method-metric pair choice to perform the cluster analysis of the data, which the closer the value of coefficient c is to 1, the more appropriate was the choice of the dissimilarity metric and the linkage method. The cophenetic correlation coefficient was calculated according to the following equation:

$$c = \frac{\sum_{i=1}^{j}(x(i,j) - \bar{x})(t(i,j) - \bar{t})}{\sqrt{\sum_{i=1}^{j}(x(i,j) - \bar{x})^2 \sum_{i=1}^{j}(t(i,j) - \bar{t})^2}} \tag{2}$$

where $x(i, j)$ is the distance between the time series i and j based on the chosen dissimilarity metric and $t(i, j)$ is the dendrogram distance between the time series i and j based on the chosen method.

Finally, to define the optimal number of clusters to perform the regionalization, the silhouettes method (Rousseeuw, 1987), the Calinski-Harabasz criterion (Calinski and Harabasz, 1974) and the variation curve of the distance between the clusters were used. Based on the variation curve of the distance between clusters by the number of clusters, it was assumed that the optimum quantity is equivalent to the number of clusters in which this variation curve remained constant. The idea of adopting this criterion is that when the derivative of this curve is practically null, there is no advantage in dividing the time series into several clusters because the variation between the clusters is not relevant. The silhouettes

method measures how similar the time series of a given cluster are in relation to the original cluster when compared to the time series of other clusters. The final value of the silhouette is the average value among the all-time series, and the values range from −1 to 1, with the best result being 1 (Equation 6):

$$S_i = \frac{(b_i - a_i)}{\max{(a_i, b_i)}} \tag{6}$$

where S_i is the silhouette value of time series i, a_i is the average distance from time series i to the time series of the origin cluster and b_i is the distance from series i to the time series that forms the other clusters.

The Calinski-Harabasz criterion, in turn, expresses the ratio between the variance between the different clusters and the variance within the different clusters. In general, based on this criterion, well-defined clusters present high variance between different clusters and small variance within clusters, and therefore, in the case of the *CH* ratio, the higher the value, the more adequate the cluster analysis was (Equation 7):

$$CH = \frac{SS_b}{SS_w} \times \frac{(N - k)}{(k - 1)} \tag{7}$$

where SS_b is the variance between clusters, SS_w is the variance between clusters, N is the number of time series analyzed and k is the number of clusters.

3. RESULTS AND DISCUSSION

3.1. DEFINITION OF THE LINKAGE METHOD

The best linkage method between the clusters was evaluated to avoid random choices and the cophenetic coefficient c of behavior, duration and severity time series of droughts were calculated for eight-time scales, three linkage methods and two databases (Figure 5). Because of the variability of the results, it is worthwhile to provide a brief explanation of how to interpret them: the c calculated from the drought behavior time series based on the 187 TRMM cells grids were 0.80 when using the average distance as the linkage method and 0.76 when using simple and complete distances, in the case of SPI-1.

From rain gauge-measured data, these values were 0.84, 0.83 and 0.60 when using the average, complete and simple linkage methods, respectively. It is noteworthy that the results show high variability when considering all combinations and as for the variation between the types of drought time series, the results tend to vary according to the time scale. For short- and medium-term droughts, the values of c are higher for behavior time series, but for long-term, the duration and severity time series presented the best results, i.e., higher c values.

Regarding the variation of *c* values between the time scales, it is important that for the behavior time series, the best results were found in the case of medium-term droughts, but there is no great difference between these results and those found in the case of short- and long-term droughts. On the other hand, when evaluating the duration and severity time series, the sensitivity of *c* is evident as a function of the change in the temporal scale, such that the results are better as the time scale increases. For long-term droughts, the values are more notable and indicate greater consistency in the analysis of clusters, while the results of short- and medium-term droughts are slightly worse.

Among the databases, it can be seen that making a direct comparison, i.e., same time scale, type of time series and linkage method, the *c* values obtained from TRMM-estimated rainfall data are predominantly higher than those calculated based on the rain gauge-measured data. It indicates that the cluster analyzes developed based on the TRMM estimates are more consistent than the analyzes developed based on the rain gauge data. Finally, regarding the variation of the coefficient *c* according to the linkage method, it is noted that the average linkage method presented the best performance.

In general, the results based on the complete linkage method performed middle, while the worst values occurred when using the simple linkage method. It can be highlighted that there is a high variation between the values of these two methods, and these values depend on the combination of the series, time scale, or database used. In addition, it is noteworthy that the results based on the average linkage method were not as sensitive to these combinations. In other words, from the simple linkage method, the coefficient *c* values calculated based on the rain gauge-measured data, for example, are 0.285, 0.535 and 0.535 for the SPI-9 behavior, duration and severity time series. However, when evaluating this result considering the SPI-48, the values exceed the order of 0.800, which shows considerable variability.

Contrary to what occurred when using the simple and complete linkage method, there is consistency in the values of the correlation coefficient between the time scales and types of drought time series when using the average linkage method. These results corroborate with Unal et al. (2003), who concluded that the average linkage method could fill gaps of other methods as it can minimize the variance within the series of the same cluster and maximize the variance between the different clusters. Several studies have been carried out based on this linkage method, and the results have been extremely satisfactory, although the purpose was to regionalize different areas based on the precipitation regime (Santos et al., 2019a) or according to the drought pattern (McGree et al., 2016; Shiau and Lin 2016; Yang et al., 2017).

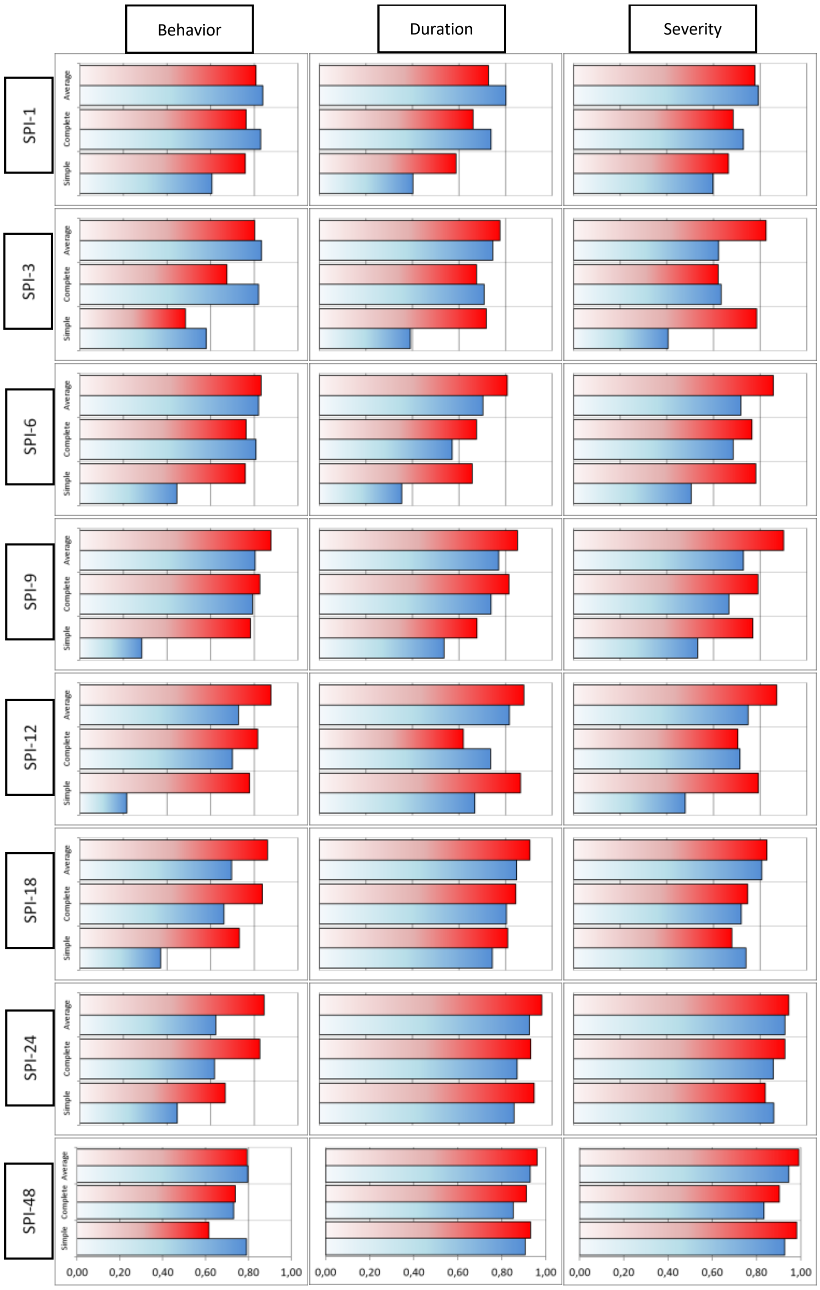

Figure 5 – Variation of the cophenetic correlation coefficient *c* for the time series of behavior, duration and severity in multiple time scales over Paraíba State (1998–2017).

3.2 DEFINITION OF NUMBER OF CLUSTERS

Based on the average linkage method, Figure 6 shows the relationship between the correlation distance between clusters, silhouette method and the Calinski-Harabasz criterion with the number of clusters for behavior, duration and severity time series over the Paraíba State (1998–2017). These results help to define the optimal number of clusters to develop an efficient cluster analysis in the region. The results based on satellite-estimated data presented shorter Pearson correlation distances, which indicates that there is greater similarity between

these time series. The variation curve of the distances between the clusters by the number of clusters related to TRMM is, in most cases, below from that obtained from the rain gauge-measured data. This difference is smaller for short-term droughts but increases when assessing medium- and long-term droughts and the duration and severity time series.

Calinski-Harabasz values tend to be higher when using TRMM-estimated data, regardless of the type of drought time series, time scale, or the number of clusters, and this scenario only changes in some cases, e.g., in the case of SPI-9 for behavior, duration and severity time series. In addition, there is a similarity between the silhouette's values with those of *CH,* and these values were predominantly higher when using TRMM-estimated data, especially for medium- and long-term droughts. It is noteworthy that the best results for *CH* and *Si* were obtained for less than five clusters.

Comparing the results between the three drought time series, the distances between the clusters are shorter for the behavior time series and longer for the duration and severity time series. For SPI-1, when evaluating four clusters, the distance between groups is about 0.45 for the behavior time series, but for the duration and severity time series, the distance is 0.55. For the SPI-12, the pattern was even more evident because after grouping the behavior time series into four clusters, with amplitudes ranged 0.25 and 0,60 for the behavior, and duration and severity time series, respectively. The results show that regardless of the time scale or database, the behavior time series can be considered more homogeneous with each other than the duration and severity time series.

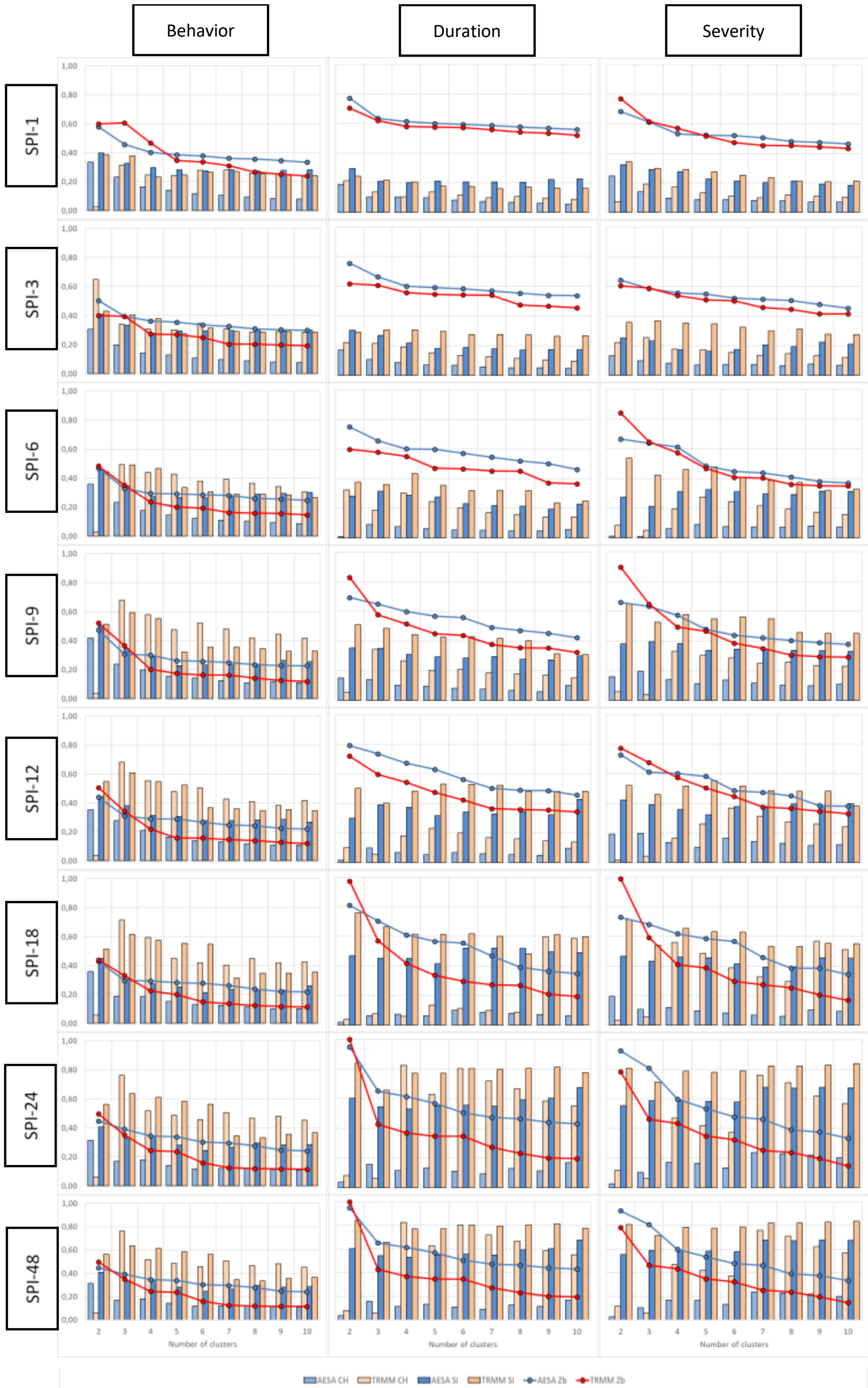

Figure 6. Relationship between the correlation distance between clusters, the silhouette criterion and the Calinski-Harabasz criterion with the number of clusters for the time series of behavior, duration and severity of droughts over Paraíba State (1998–2017).

Concerning *CH* values, the results indicate that for short- and medium-term droughts, the values tended to be higher for the drought behavior time series. Also, the *CH* values

obtained from the TRMM-estimated data had greater variability between the types of drought time series compared to the results obtained from the rain gauge-measured data. Regarding the silhouettes method, there is no significant variation between the results for the same time scale, except for what was obtained when evaluating long-term droughts. In this case, the values for the duration and severity time series were higher than those found when evaluating the behavior time series, as found for the *CH* (Figure 6).

For the behavior time series, there is a kind of stability in the distance values between the clusters for a small number of groups, mainly for short- and medium-term droughts. This means that the curves, in the figure, relate the distance between the clusters and their number become less steep (almost constant) from four clusters, indicating that it is unnecessary to divide the TRMM cells grid or rain gauges into more groups. For example, for the SPI-3 behavior time series the distances between four clusters are 0.25 based on TRMM-estimated data and 0.35 based on rain gauge-measured data (Figure 6), whereas for ten clusters, the distances are almost the same, i.e., 0.30 based on TRMM-estimated data and 0.20 based on rain gauge-measured data.

Therefore, as the distance between the clusters has been subtly altered, it is irrelevant to divide the TRMM cells grid and the rain gauges into more groups. In contrast, when developing the same analysis for the SPI-48, the distances between the clusters using four and ten groups already vary from 0.40 (TRMM) to 0.20 (rain gauges), which shows a greater jump in the curve compared to the results presented for short- and medium-term droughts. For duration and severity time series, this pattern was maintained, and for short-term and medium-term droughts, the values of correlation distance stabilized with a smaller number of groups. For long-term droughts, there was a greater distinction between the series, and the stability of the curve was found with a higher number of clusters.

It is worth noting that concerning the number of clusters, there was a change in the values of the silhouettes at multiple time scales based on rain gauge-measured data, but choose the number of clusters below five groups still behaves as one of the most appropriate choices in most cases.

From the use of these three methos (i.e., variation curve, *CH* and *Si*) to define the number of clusters, it is noted that using few clusters is the adequate alternative in most cases. Since the territorial division of Paraíba composed of four mesoregions, four were adopted as the number of clusters. For this quantity, the values of the silhouettes and the *CH* criterion are expressive, as well as the variation curves tend to be less steep, which makes a choice effective from the perspective of different methods. Although there are cases in which this

quantity is not appropriate, it should be noted that the choice was based on the results of the 48 cluster analyzes, which makes impossible to attend all cases. In addition, the capacity of TRMM-estimated data to reproduce the same pattern of results as rain gauge-measured data stands out.

3.3. ANALYSIS OF DROUGHT BEHAVIOR TIME SERIES

After defining the dissimilarity metric (i.e., Pearson correlation coefficient), the linkage method (i.e., average linkage method), and the optimal number of clusters (i.e., four), the distribution process of the clusters was carried out based on the time series of behavior, duration and severity of droughts over the region. Initially, Figure 7 shows the results of the hierarchical cluster analysis developed for the drought behavior time series based on rain gauge-measured and TRMM-estimated data for different time scales. It was observed a variation between the results obtained when considering the different SPI indices and the rainfall datasets.

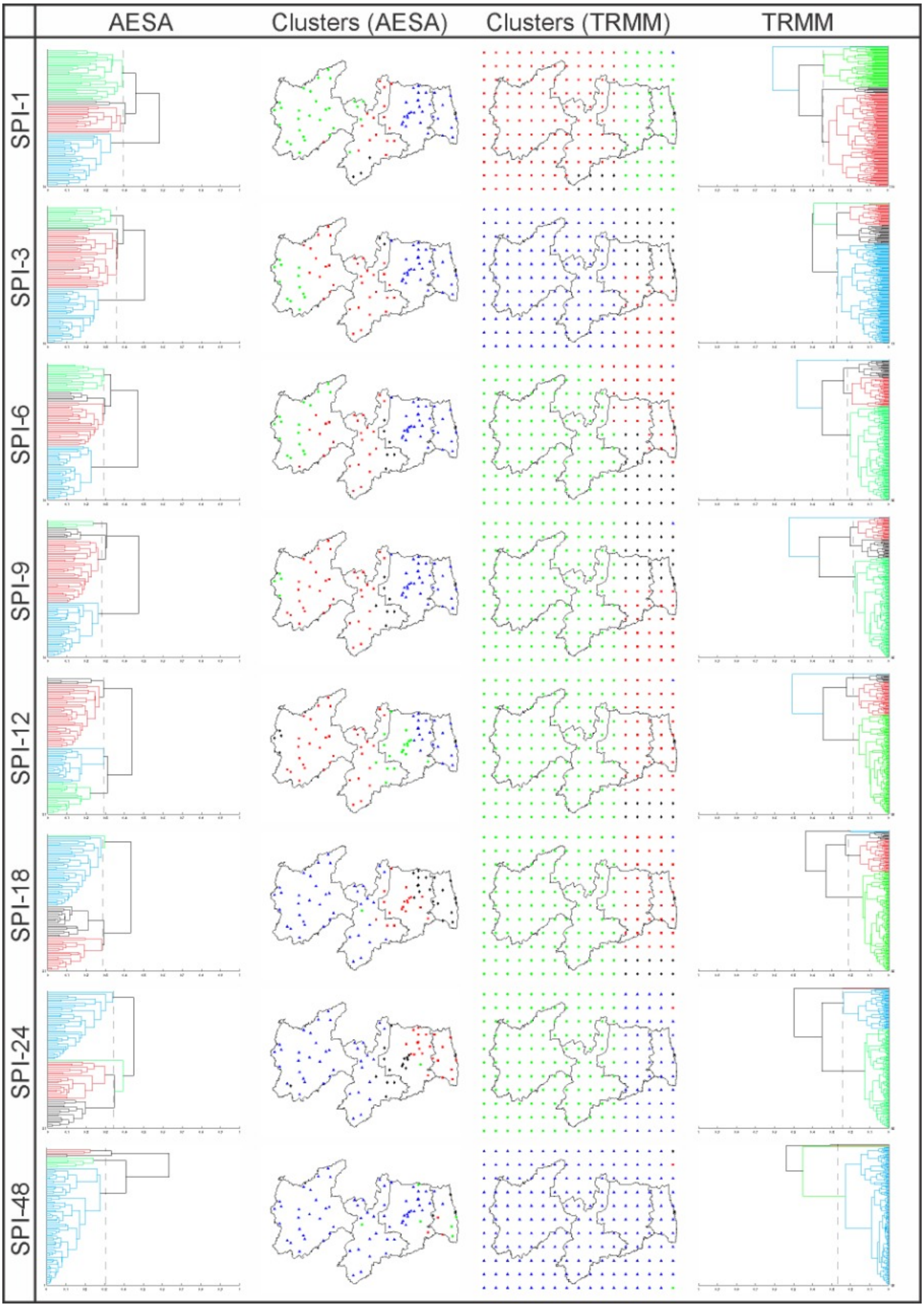

Figure 7. Analysis of hierarchical cluster and its dendrograms using four clusters based on the time series of drought behavior over Paraíba State (1998–2017).

For short-term droughts, there is a correspondence between the spatial distribution of clusters and the mesoregions of Paraíba State (Figure 1). Based on rain gauge- measured data, the results indicate that at a distance of 0.50 between clusters, there is a group that encompasses the mesoregions of Sertão Paraibano and Borborema (♦ ■ ●), while Agreste Paraibano and Mata Paraibana are covered by another cluster (▲). In the case of SPI-3, the Sertão was divided in half by an area to the west (●) and another to the east (■), such that the latter extends towards the coast of Paraíba and covers the entire Borborema to the west of Agreste Paraibano. In the case of SPI-6, the difference in the behavior of the clusters on the border between Borborema and Agreste Paraibano becomes clearer (♦).

When assessing the dendrograms, the pattern in the inland of Paraíba State is more heterogeneous than in the regions closest to the coast. In the case of SPI-3 and SPI-6, the rain gauges located in Agreste Paraibano and Mata Paraibana only differ to each other at a distance of less than 0.25, while at a distance of 0.30 there are already two clusters dividing the inland of Paraíba State. Based on TRMM-estimated data, the time series tend to be more homogeneous when compared to the results obtained from the rain gauge-measured data and the results show a good correspondence between the spatial distribution of the clusters and the mesoregions of Paraíba (Figure 1).

Still based on TRMM-estimated data, it is noteworthy that, except for the SPI-1 results, where there was a distinction between time series in Sertão Paraibano (■) and south of Borborema (♦), these two mesoregions were always grouped in a cluster, differently from the results found based on rain gauge- measured data. These results indicate that there is greater variability between the drought behavior in the mesoregions of Agreste Paraibano and Mata Paraibana. It is noted that although the TRMM satellite has shown an accuracy in separating the regions of Sertão and Borborema from the mesoregions of Agreste and Mata Paraibana, there was a certain inaccuracy when estimating which of these two mesoregions were more homogeneous with each other.

For medium-term droughts, the distances between four clusters were the shortest among the time scales, which indicates greater similarity between the series over the region. Based on rain gauge-measured data, the division of Paraíba State between the mesoregions of Sertão Paraibano and Borborema, and the region of Agreste Paraibano and Mata Paraibana became increasingly evident. There is a cluster formed at western of Sertão Paraibano, and the other part of this mesoregion is covered by another cluster (■) that extends to Agreste Paraibano. In Mata Paraibana, the behavior is the same for SPI-9 and SPI-12, and the existence of only one cluster over the entire area is noted (▲).

Based on TRMM-estimated data, the distances found between the clusters are smaller than those found based on rain gauge-measured data. At a correlation distance of 0.40, the TRMM series are grouped into a large group that covers the entire state, which differs from the results based on rain gauge-measured data. Despite the differences, the results obtained from the TRMM-estimated data demarcate the division of Paraíba State into two major regions: one located in the interior and formed by Sertão and Borborema (●), and the other on the coast of Paraíba State, standing out that the region close to the coast was divided into two zones: one located in the north and the other in the south.

It is noteworthy that the satellite did not identify the particularities of western Sertão Paraibano and Agreste Paraibano and Mata Paraibana, but just as for short-term droughts, it identified that clusters located in the inland of the state are more homogeneous than the clusters near to the coast. Finally, the results show that there is a high variation for long-term droughts in relation to the results of short- and medium-term droughts, especially in the case of SPI-48. Based on rain gauge-measured data, the spatial distribution of the clusters for the SPI-18 and SPI-24 indices are similar, but the results of the SPI-48 have a more particular pattern.

For SPI-18 than for SPI-24, the regions of Borborema and Sertão Paraibano showed less similarity to each other despite being mostly covered by a cluster (▲). From the border between Borborema and Agreste Paraibano to the central portion of this mesoregion, there is a cluster, while from the center of Agreste to the coast, there is another group. For the SPI-48, the behavior is more intriguing, and the reason is that there is a predominance of a group (▲) in all mesoregions of the state, covering from the Sertão Paraibano to the coast. In Mata Paraibana, four different clusters could be found, which highlights the variability of the drought pattern in this region.

Based on the TRMM-estimated data, the division of Paraíba State based on SPI-18 and SPI-24 into two regions is clearer: one formed by Sertão Paraibano and Borborema (●) and the other by Agreste and Mata Paraibana (♦ ■ ▲). From the dendrograms, the clusters are more similar to each other when dealing with the Sertão Paraibano and Borborema and that these will only start to differentiate at a correlation distance of 0.15. When evaluating the SPI-48, almost all TRMM grids are grouped in a cluster (▲), as well as in the results obtained based on rain gauge-measured data. This indicates that for the long-term drought behavior time series, there is a high similarity pattern between the series over the region.

One of the possible explanations for the distances between the clusters in the case of short-term droughts to be so high is that as the behavior of these SPI series is very variable, it

is expected that the time series have less similarity. In other words, any disturbance in the precipitation time series can cause an extremely dry or wet SPI value to appear, and this can lead to differences in the similarity between the time series. Evaluating medium- and long-term droughts, except for rare cases, the time series tend to behave in the same way due to the accumulation of precipitation accumulated over time, which makes the series have high similarity.

The pronounced similarity of the drought behavior time series based on TRMM-estimated data can be linked to the algorithm employed by the satellite, which can tend to compensate for the precipitation values between the regions. In this case, as the behavior time series are grouped according to the similarity of the SPI variation over time, the compensation may have made the series more similar to each other. When using rain gauge-measured data, on the other hand, point variations are captured in a more particular way, and this increases the dissimilarity between the series of station's behavior.

3.4. ANALYSIS OF DROUGHT DURATION TIME SERIES

Figure 8 shows the result of the hierarchical cluster analysis for the drought duration time series based rain gauge-measured and TRMM-estimated data for different time scales. As discussed in Figure 6, the correlation distances between four clusters are greater than those found based on the analysis of the behavior time series. It is noteworthy that the spatial distribution of the clusters based on the drought duration time series differs in some situations from the configuration obtained when evaluating the drought behavior time series. This result is relevant because it shows that a given rain gauge (or TRMM grid) may be highly similar to another concerning the drought behavior time series but differ when assessing the drought duration time series.

For short-term droughts, the results obtained from the times series of duration and behavior of droughts have changed, and this has occurred in an evident way when based on rain gauge-measured data. Based on this dataset, there is a change in the spatial distribution of the clusters, such that for SPI-1, Sertão Paraibano and Borborema are mostly covered by only one cluster (▲), while Mata Paraibana and Agreste Paraibano are formed by two distinct zones, one to the west (♦) and the other to the east (▲).

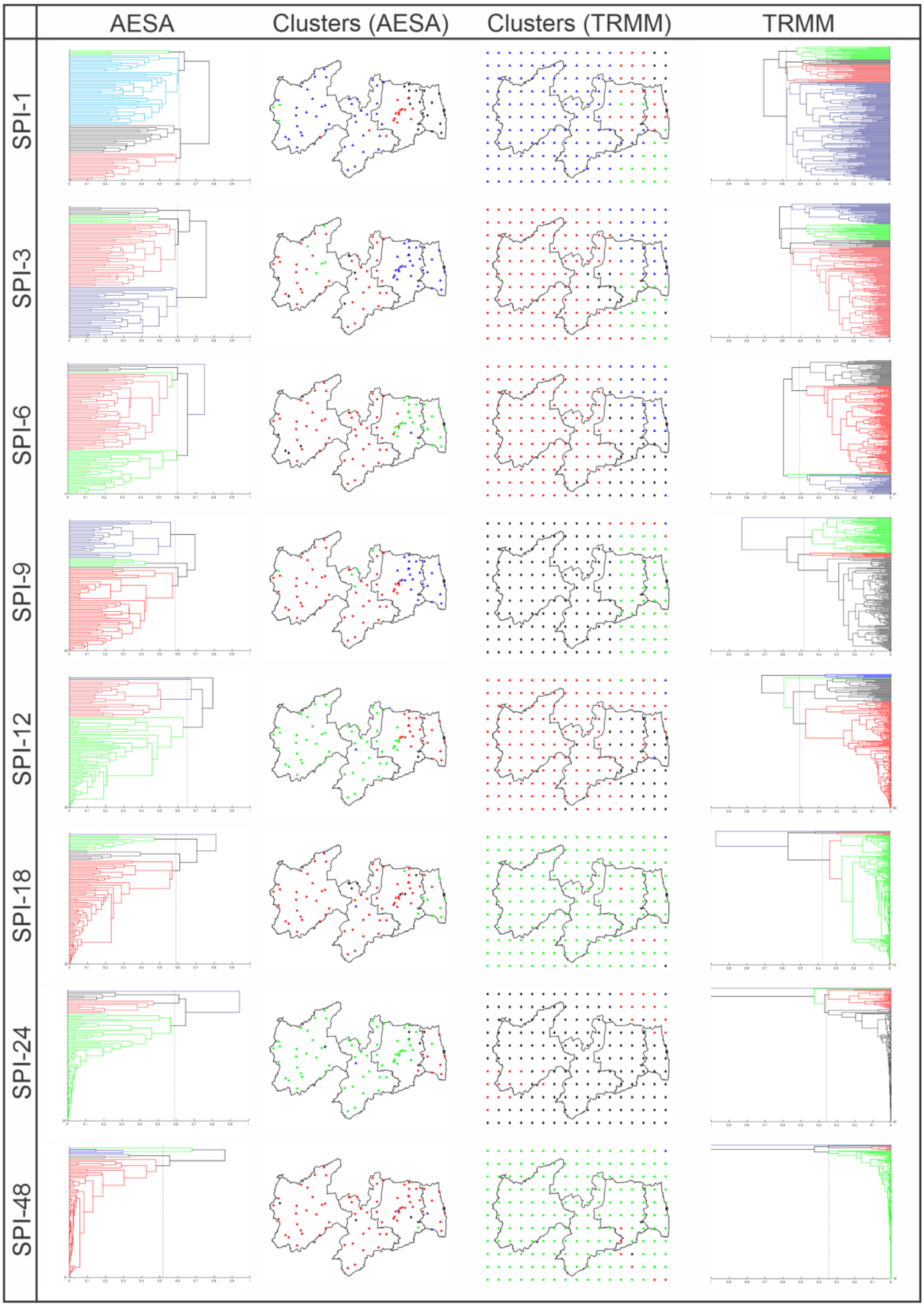

Figure 8. Analysis of hierarchical cluster and its dendrograms using four clusters based on the time series of drought duration over Paraíba State (1998–2017).

For SPI-6 can be noted that the Sertão Paraibano and Borborema were divided into three clusters and grouped in a cluster (■), while a cluster covered the Mata Paraibana and Agreste Paraibano and were formed mostly by another zone (●). For SPI-3, the distribution of

clusters is more irregular compared to the pattern of SPI-1 and SPI-6: the Sertão is divided into three regions, one in the southwest (♦), the other in the center (■), and another in the northeast (●), while Agreste and Mata Paraibana are composed by single cluster (▲). This result differs from that found in Figure 7, since the grouping was more consistent with the limits of the mesoregions of Paraíba State, especially in the case of the Sertão and Borborema mesoregions.

However, it is interesting to note that there are indications that the regions of Mata and Agreste Paraibano continue to have homogeneous behavior between them, while Sertão and Borborema have a pattern of higher dissimilarity. Moreover, it is important to emphasize that the mesoregions of Mata Paraibana and Agreste Paraibano are no longer so similar between themselves when compared to the similarity that exists between the Sertão Paraibano and Borborema, a fact that differs from the pattern that was obtained when evaluating the drought behavior time series.

From the TRMM-estimated data, changes were noted regarding the spatial distribution of clusters over Paraíba State, and in general, what is noticeable is that the regions of the Sertão and Borborema tend to have a large part of their territory composed of a cluster. In addition, in comparison to the cluster analysis of the drought behavior time series, it is clear that the spatial distribution of the clusters was maintained, especially in the case of SPI-6. In the case of SPI-1, there was a great variation in the distribution of clusters in Agreste and Mata Paraibana, which started to be divided into three clusters (♦ ■ ●); in the case of SPI-3, a cluster appeared between Agreste Paraibano and Borborema (♦).

For the SPI-6, it is worth noting that there is greater similarity between the clusters that cover the mesoregions of Sertão, Borborema and Agreste (♦ ■). The other cluster covers the north of Agreste, and a large part of Mata Paraibana (▲) has a unique behavior compared to the others. This result shows that, differently from what occurred when evaluating the behavior time series of short-term droughts, already for the analysis of the duration series of the SPI-3 and SPI-6 indices, there was a tendency to zone most of Paraíba State in a single cluster, which it is a result that was obtained when evaluating the long-term drought behavior time series.

For medium-term droughts and based on rain gauge-measured data, there is similarity regarding the spatial distribution of the clusters over Paraíba State compared to the results in Figure 7, but some differences need to be scored. For SPI-9, the region of Sertão Paraibano and Borborema started to be composed by a single cluster (■), and this cluster crosses the border between these mesoregions and extends to the center of Agreste Paraibano. From this

region to the coast, another cluster (▲) is formed that covers Agreste Paraibano and Mata Paraibana. For SPI-12, the change in the spatial distribution of the clusters intensifies such that from the Sertão to the central portion of Agreste, there is a more representative cluster (●), and from Agreste to the coast, there is another cluster (■), as well as in the case of SPI-9.

Thus, differently from the results shown in Figure 7, the state of Paraíba started to be divided into less representative clusters. However, from the dendrograms, it can be seen that the interior mesoregions showed greater dissimilarity between them when compared to the pattern of the mesoregions closer to the coast, as found for the drought behavior time series. Based on TRMM-estimated data, the division of Paraíba State into two major regions is even more evident, especially when evaluating SPI-9. In a way, these results corroborate those found by using rain gauge-measured data, considering that the formation of two main clusters on Paraíba State was identified.

The results indicate that the Sertão Paraibano and Borborema are more homogeneous among themselves than the regions of Agreste and Mata Paraibana, as obtained in the analysis of the drought behavior time series. Moreover, the dendrogramic distances between the clusters over Paraíba have high stickiness when evaluating long-term droughts, but these are the smallest when only four clusters are evaluated. This implies that when considering a distance between the clusters of 0.80, the short- and medium-term drought duration time series would be grouped into a single cluster, while when evaluating SPI-18, SPI-24 and SPI-48, the time series obtained based on rain gauge-measured data and satellite-estimated data are subdivided into at least two clusters, which highlights the heterogeneity of long-term droughts.

On the other hand, at the level of four clusters, these distances are not pronounced, and this shows that the rain gauges and the TRMM grids have unique behavior, which makes a distinction between clusters with a high dissimilarity. Based on rain gauge-measured data, the results obtained for SPI-18 and SPI-24 are more similar, while those for SPI-48 have particularities. In general, for SPI-18, the Sertão, Borborema and Agreste are covered by a cluster (■), while Mata Paraibana is composed of another (●), results similar to those obtained for the SPI-24. For SPI-48, one cluster covered a large part of the state (■), and the others were concentrated in the center-south portion of Agreste, as well as in the case of Figure 7.

Based on TRMM-estimated data, Paraíba State is covered by the same cluster, and this applies to the SPI-18, SPI-24 and SPI-48 indices. In detail, except a grid in the center of Agreste (■) for SPI-18, from the southwest region of Sertão and north of Mata Paraibana (■) for SPI-24 and from south of Agreste (■) for SPI-48, all regions showed the same pattern of

variation as to the drought duration time series over time. Although there are differences, TRMM-estimated data identified that there is a cluster over Paraíba State,but it was not so accurate to identify a unique pattern of the mesoregion of Mata Paraibana.

3.5. ANALYSIS OF DROUGHT SEVERITY TIME SERIES

Finally, Figure 9 shows the result of the hierarchical cluster analysis for the drought severity time series based on rain gauge-measured and TRMM-estimated data for the different time scales. In general, there is a great similarity between the results of the cluster analysis of the drought severity and duration time series (Figure 8). It is worth noting that for short-, medium- and long-term drought severity time series, the distances between the first two clusters based on TRMM-estimated data are greater than those obtained based rain gauge-measured data, and this result occurred in a significant way when evaluating SPI-1, SPI-6, SPI-9, SPI-18 and SPI-48.

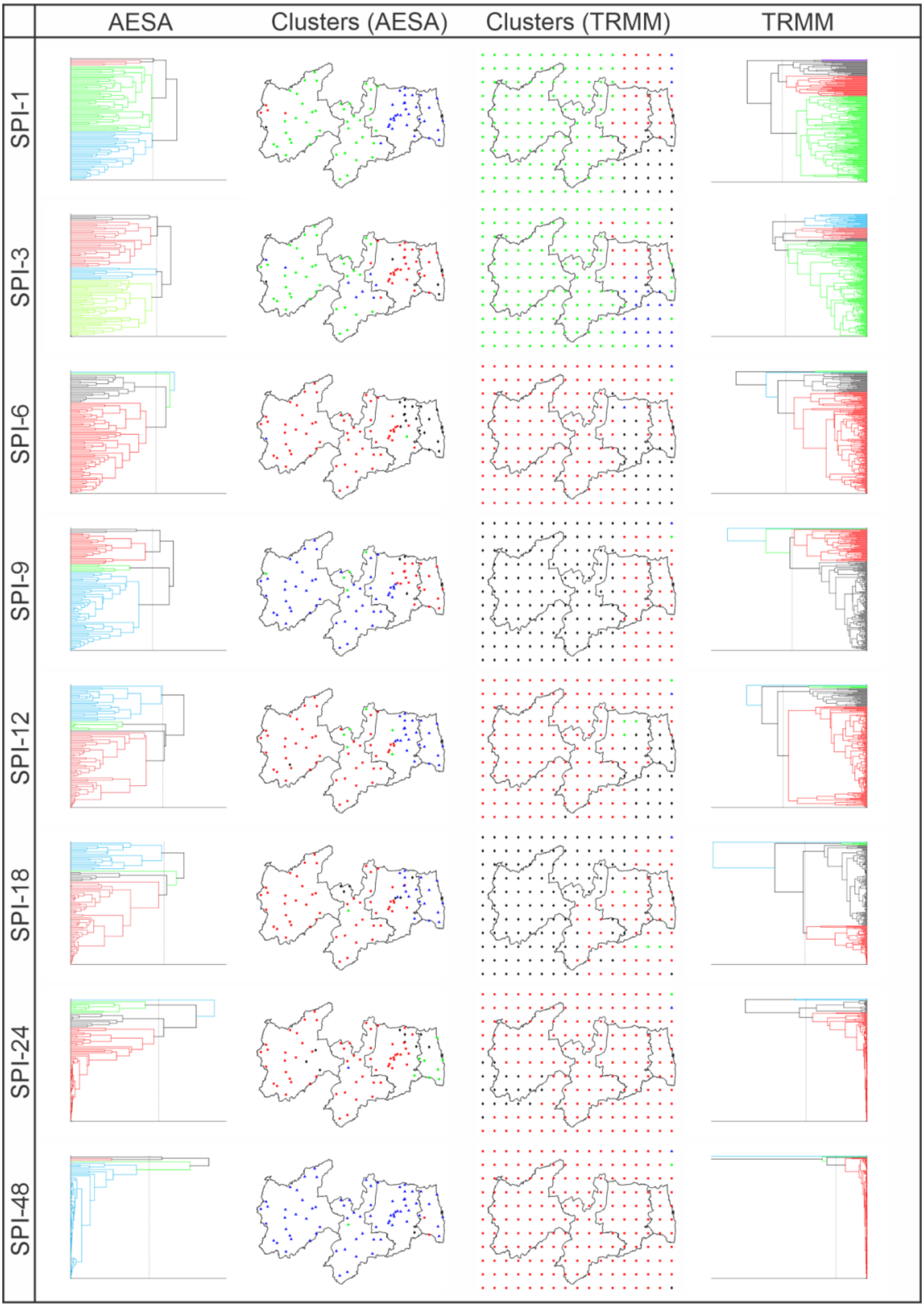

Figure 9. Analysis of hierarchical cluster and its dendrograms using four clusters based on the time series of drought severity over Paraíba State (1998–2017).

Based on rain gauge-measured data, it is noted that for SPI-1, Paraíba was divided into two clusters: one of which covered much of the Sertão and Borborema (●) and the other the Mata and Agreste Paraibano (▲). The spatial pattern of the clusters in the case of SPI-3 was similar to SPI-1, and the division of the state into two main regions is notorious, but the central region of Borborema (▲) started to behave a little more distinctly from the interior of the state. As for SPI-6, the center-west of Agreste also started to behave more similarly to Sertão and Borborema (■) and more dissimilar to regions close to the coast. Based on satellite-estimated data, the regions of the Sertão Paraibano and Borborema were covered by a single cluster, i.e., SPI-1 (●), SPI-3 (●), SPI-6 (■), while that Agreste and Mata Paraibana showed greater variability when compared to the results of the drought duration time series.

In the case of medium-term droughts, the distances between the clusters have the same order of magnitude as the drought duration time series. Based on rain gauge-measured data, there is once again a high similarity between the results obtained in Figures 8 and 9. For SPI-9, there is a small change in the north and central portion of the Agreste, but the same regionalization when evaluating the drought duration and severity time series. For the SPI-12, two main clusters stand out over the region: one located from Sertão to Agreste (■) and another from Agreste to the coast (▲). Regarding the results based on TRMM-estimated data, for both SPI-9 and SPI-12, the Paraíba State was divided into two major regions.

The region closest to the coast has greater variability than the interior, especially in the case of SPI-9. When comparing the results between the datasets, there was high agreement on the part of the satellite when subdividing Paraíba State into homogeneous zones. For SPI-9, however, the most significant disagreement with rainfall data was to the north of the Borborema zone, as this zone was incorporated into the cluster that covers the interior of the state (♦). For long-term droughts, it is noted that based rain gauge-measured data, for the SPI-18 Paraíba is covered by two clusters, one that runs from the Sertão to the center of Agreste (■) and the other that goes from the east of Agreste to the coast of Paraíba (▲).

For SPI-24, in turn, there are two distinct clusters in the vicinity of Mata Paraibana, such that one is to the north (♦) and the other to the south (●). For the SPI-48, as well as for the results of the drought behavior and duration time series, a cluster covers the entire Paraíba (▲). In general, the increase in the time scale of the SPI indices causes the entire state to behave in the same way concerning the drought severity time series. Based on the TRMM-estimated data, Paraíba tends to be grouped into a single cluster. For SPI-18, however, this pattern is not so evident, and one can see the existence of a cluster that covers the Sertão, the

north and southwest of Borborema (♦), and another that extends from the central portion of Borborema to the coast of Paraíba (■). For SPI-24, except for southwestern Sertão (♦), all regions are members of the same cluster (■), and this is repeated when evaluating SPI-48.

It is valid to point out that some works developed in the literature have already zoned Paraíba State in different homogeneous regions based on the pluviometric regime, and the results are intriguing. Keller Filho et al. (2005), for example, delimited about 25 rainfall homogeneous zones over Brazil, of which ten are in the NEB, and four are over Paraíba State. The results indicate that one of the zones is located on the coast of Paraíba, another covers a large part of Agreste Paraibano and the others cover the areas of Borborema and Sertão Paraibano. Reboita et al. (2010) pointed out that Paraíba State is inserted in two main regions: one close to the coast and the other in the Northeastern Sertão.

The coastal region, which presents the Intertropical Convergence Zone as its main climatic system, has an average annual rainfall greater than 1500 mm, while the Northeastern Sertão area has rainfall less than 500 mm, which corroborates our study and the results found by Santos et al. (2019b). In NEB, Araújo and Souza (2012) identified four different zones regarding the pattern of precipitation, two of which are distributed over Paraíba State. In this study, it was noticed that the coastal area has a distinct pattern when compared to the interior of the state, a result that corroborates with our research. The caveat is that the coastal area consists of a less significant area than the other region that covers the interior and much of the state, which indicates that Paraíba tends to behave very homogeneously.

In Paraíba, Macedo et al. (2010) delimited three different zones: one covers Mata Paraibana and the eastern half of Agreste, another is located from the western half of Agreste to Borborema, and the third is located in the Sertão Paraibano. Despite this unconventional division in relation to the separation of the Sertão Paraibano from Borborema, the researches emphasize that these regions are the most similar to each other and that the behavior found on the coast has more unique characteristics, similar to the results found in this paper. Using the TRMM-estimated data, Santos et al. (2019a) showed an evident differentiation of precipitation in the regions of Agreste and Mata Paraibana from the behavior of the regions of Borborema and Sertão, and that this clustering pattern can be found even when evaluating different time scales.

The conclusions of these studies reaffirm the results found in this research. In general, there is a zoning pattern in the Paraíba State in two regions, one comprising Sertão and Borborema, and the other comprising Agreste and Mata Paraibana. The TRMM-estimated data identified this behavior at multiple scales and for different types of drought time series.

The results may be related to several factors, such as the influence of altitude and the Borborema Plateau, among others. This formation blocks the effects of atmospheric systems and influences the regime of precipitation and droughts in the region. In addition, factors such as the proximity of the regions to the ocean or the performance of different climatic systems may have caused this pattern of grouping. In this way, it is proved that the TRMM estimates identified homogeneous zones as to the drought behavior, duration and severity.

4. CONCLUSIONS

This study evaluated the performance of TRMM rainfall product for monitoring drought over Paraíba State using hierarchical cluster analysis to identifying areas with homogeneous behaviors, duration and severity of droughts on eight time scales over Paraíba State (1998–2017). It was possible to regionalize Paraíba State in different homogeneous zones based on the drought behavior, duration and severity in multiple time scales using rain gauge-measured and TRMM-estimated data. In general, it was noticed that regionalizing the Paraíba State in four different regions is an adequate choice for the work, and the results obtained are similar to the spatial distribution of the politically used mesoregions. There is a strong tendency to divide the state into two large regions, one formed by Mata Paraibana and Agreste Paraibano and another by the Sertão Paraibano and Borborema. On the other hand, this division is more evident when assessing short-term droughts, because based on long-term droughts, there is a tendency to group the entire state into a single cluster.

The TRMM-estimated time series are more similar to each other and point out that the Sertão and Borborema mesoregions have greater homogeneity between them, while the results obtained based on rain gauge-measured data have greater variability and point out that the Mata Paraibana and Agreste mesoregions are more similar. Factors such as proximity to the ocean, the performance of macro-, meso- and micro-scale climatic systems, and the configuration of the local relief are potential influencers of the pattern of occurrences of droughts and rains in the region, especially the Planalto da Borborema as a determining agent. Finally, it is concluded that the precipitation estimates of the TRMM satellite are a valuable source of data to regionalize and identify the drought pattern and the state of Paraíba and that more studies of this type should be carried out to monitor these phenomena more accurately from satellite data.

The importance of evaluating the spatial distribution of the clusters is emphasized considering the different drought series in multiple time scales since the integrated discussion allows for an increased understanding of the drought pattern and its characteristics.

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